

Day 10: Additional Scaling Issues

Kenneth Benoit

Essex Summer School 2011

July 22, 2011

Problems to solve I: Conditional (non-)independence

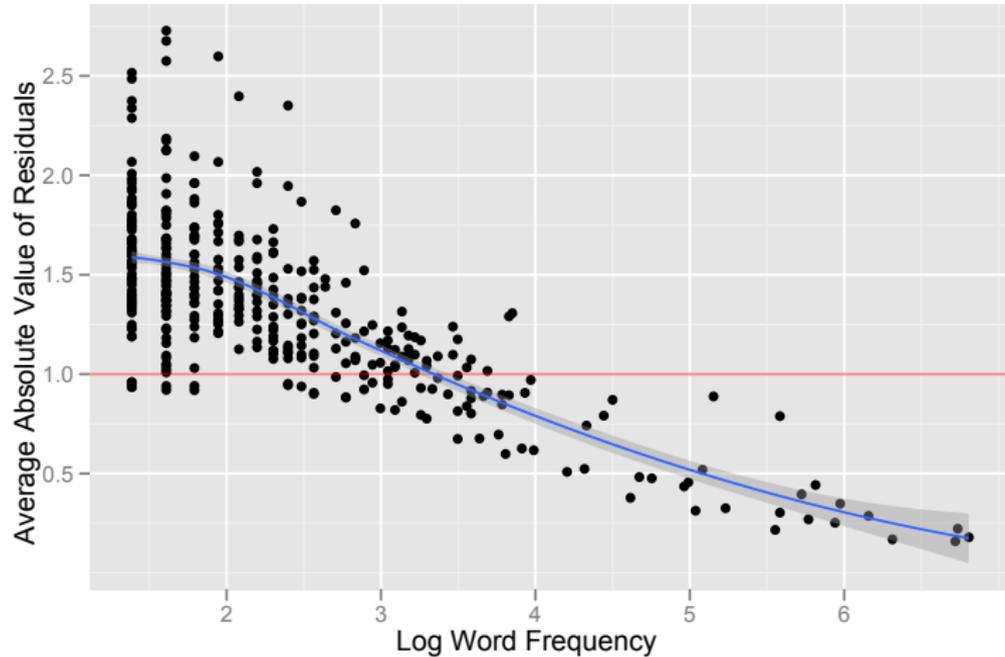
- ▶ Words occur in order
In occur words order.
Occur order words in.
“No more training do you require. Already know you that which you need.” (Yoda)
- ▶ Words occur in combinations
“carbon tax” / “income tax” / “inheritance tax” / “capital gains tax” / “bank tax”
- ▶ Sentences (and topics) occur in sequence (extreme serial correlation)
- ▶ Style may mean means we are likely to use synonyms – very probable. In fact it's very distinctly possible, to be expected, odds-on, plausible, imaginable; expected, anticipated, predictable, predicted, foreseeable.)
- ▶ Rhetoric may lead to repetition. (“Yes we can!”) – anaphora

Problems to solve II: Parametric (stochastic) model

- ▶ Poisson assumes $\text{Var}(Y_{ij}) = \text{E}(Y_{ij}) = \lambda_{ij}$
- ▶ For many reasons, we are likely to encounter overdispersion or underdispersion
 - ▶ **over**dispersion when “informative” words tend to cluster together
 - ▶ **under**dispersion could (possibly) occur when words of high frequency are uninformative and have relatively low between-text variation (once length is considered)
- ▶ This should be a *word*-level parameter

Overdispersion in German manifesto data

(from Slapin and Proksch 2008)



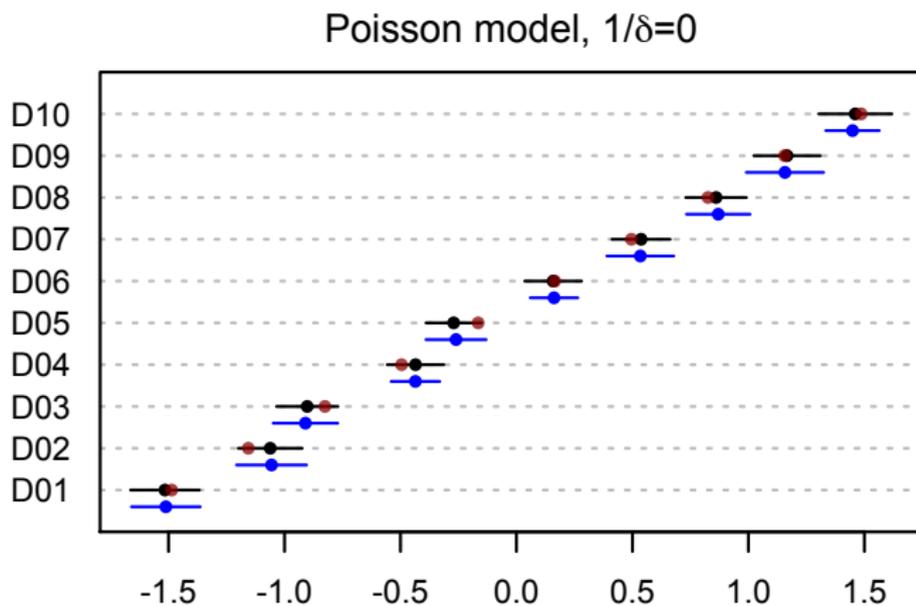
How to account for uncertainty?

- ▶ Don't. (SVD-like methods, e.g. correspondence analysis)
- ▶ Analytical derivatives
- ▶ Parametric bootstrapping (Slapin and Proksch, Lewis and Poole)
- ▶ Non-parametric bootstrapping
- ▶ (and yes of course) Posterior sampling from MCMC

Steps forward

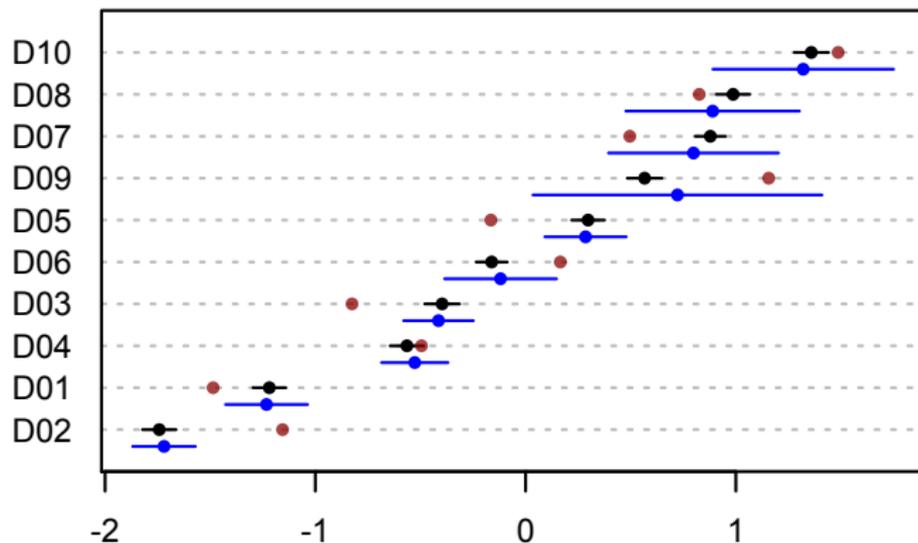
- ▶ Diagnose (and ultimately treat) the issue of whether a separate variance parameter is needed
- ▶ Diagnose (and treat) violations of conditional independence
- ▶ Explore non-parametric methods to estimate uncertainty

Diagnosis I: Estimations on simulated texts



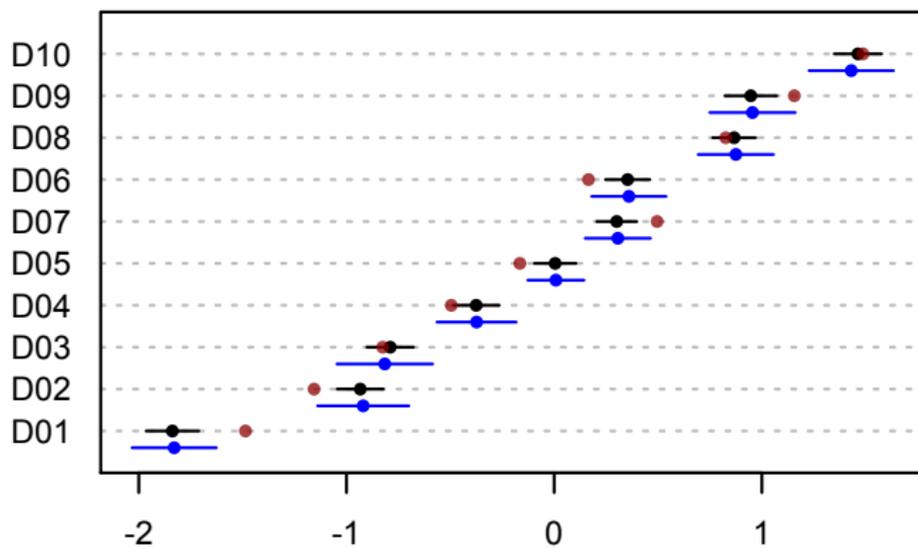
Diagnosis I: Estimations on simulated texts

Negative binomial, $1/\delta=2.0$

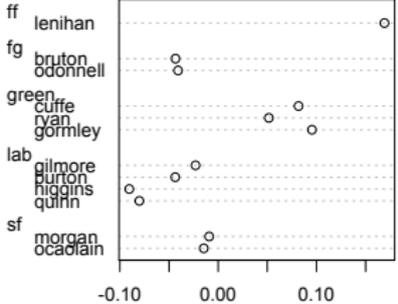


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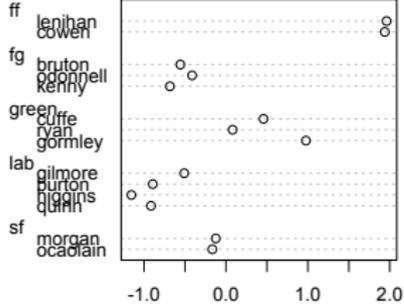
Negative binomial, $1/\delta=0.8$



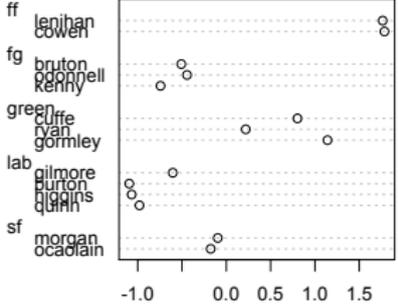
Diagnosis 2: Irish Budget debate of 2009



Wordscores LBG Position on Budget 2009



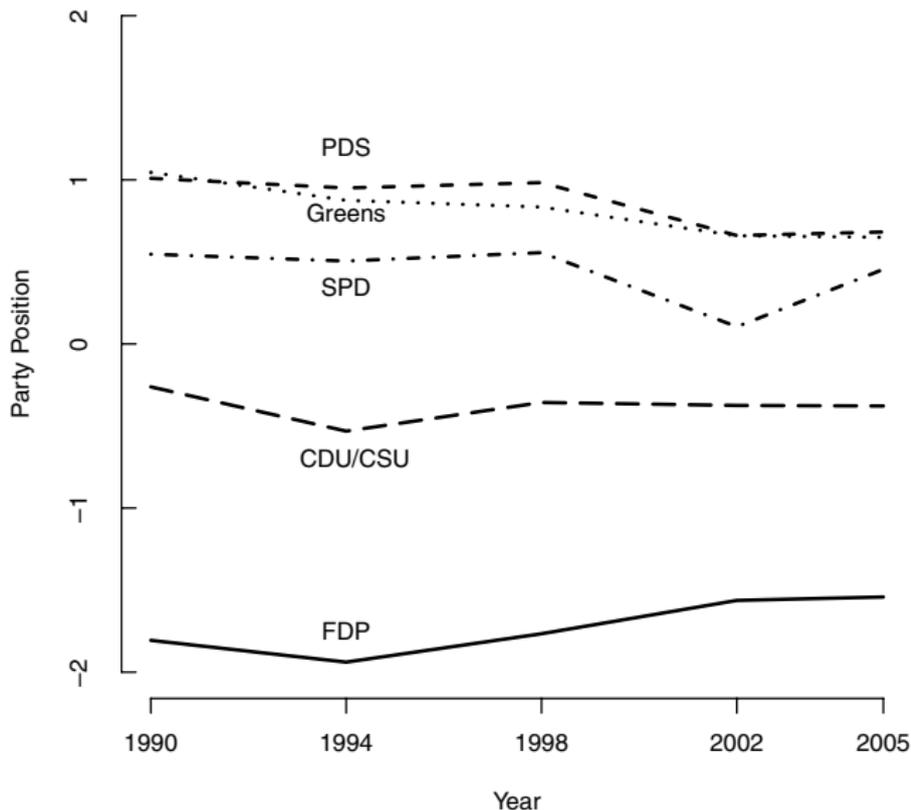
Normalized CA Position on Budget 2009



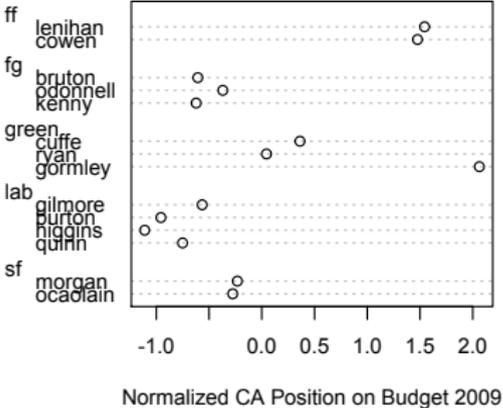
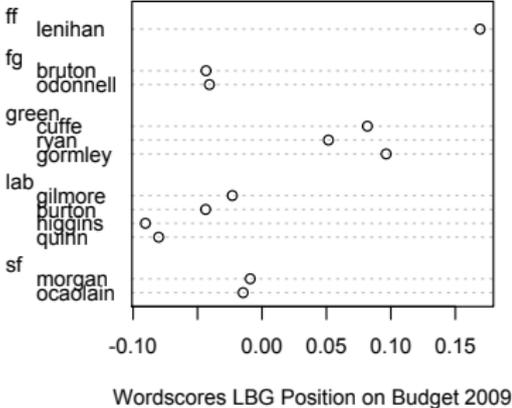
Classic Wordfish Position on Budget 2009

Diagnosis 3: German party manifestos (economic sections)

(Slapin and Proksch 2008)



Diagnosis 4: What happens if we include irrelevant text?



Diagnosis 4: What happens if we include irrelevant text?



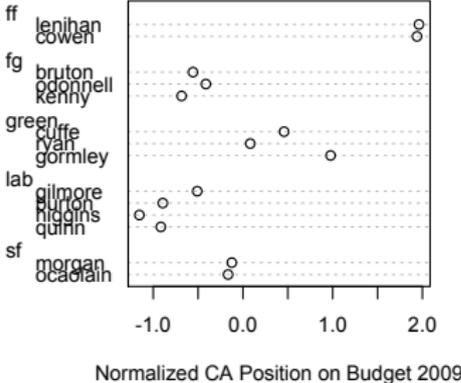
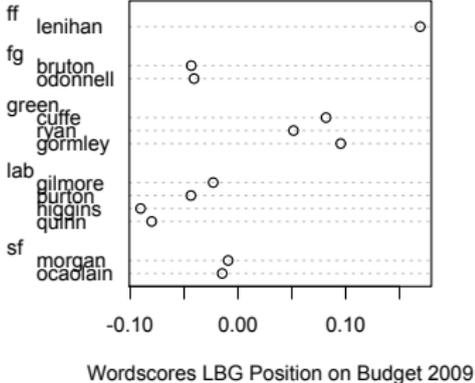
John Gormley: leader of the Green Party and Minister for the Environment, Heritage and Local Government

“As leader of the Green Party I want to take this opportunity to set out my party’s position on budget 2010. . .”

[772 words later]

“I will now comment on some specific aspects of my Department’s Estimate. I will concentrate on the principal sectors within the Department’s very broad remit . . .”

Diagnosis 4: Without irrelevant text



The Way Forward

- ▶ Parametric Poisson model with variance parameter (“negative binomial” with parameter for over- or under-dispersion at the *word* level, could use CML)
- ▶ Block Bootstrap resampling schemes
 - ▶ text unit blocks (sentences, paragraphs)
 - ▶ fixed length blocks
 - ▶ variable length blocks
 - ▶ could be overlapping or adjacent
- ▶ More detailed investigation of feasible methods for characterizing fundamental uncertainty from non-parametric scaling models (CA and others based on SVD)

The Negative Binomial model

- ▶ Generalize the Poisson model to:

$$f_{nb}(y_i | \lambda_i, \sigma^2) \text{ where :}$$

- ▶ σ^2 is the variability (a new parameter v. Poisson)
- ▶ λ_i is the expected number of events for i
- ▶ λ is the average of individual λ_i s
- ▶ Here we have dropped Poisson assumption that $\lambda_i = \lambda \forall i$
- ▶ **New assumption: Assume that λ_i is a random variable following a *gamma* distribution (takes on only non-negative numbers)**
- ▶ For the NB model, $\text{Var}(Y_i) = \lambda_i \sigma^2$ for $\lambda_i > 0$ and $\sigma^2 > 0$

The Negative Binomial model cont.

- ▶ For the NB model, $\text{Var}(Y_i) = \lambda_i \sigma^2$ for $\lambda_i > 0$ and $\sigma^2 > 0$
- ▶ How to interpret σ^2 in the negative binomial
 - ▶ when $\sigma^2 = 1.0$, negative binomial \equiv Poisson
 - ▶ when $\sigma^2 > 1$, then it means there is **overdispersion** in Y_i caused by correlated events, or heterogenous λ_i
 - ▶ when $\sigma^2 < 1$ it means something strange is going on
- ▶ When $\sigma^2 \neq 1$, then Poisson results will be inefficient and standard errors inconsistent
- ▶ Functional form: same as Poisson

$$E(y_i) = \lambda$$

- ▶ Variance of λ is now:

$$\text{Var}(y_i) = \lambda_i \sigma^2 = e^{X_i \beta} \sigma^2$$

Problems to Solve III: Integrating non-parametric methods

- ▶ Non-parametric methods are algorithmic, involving no “parameters” in the procedure that are estimated
- ▶ Hence there is no uncertainty accounting given distributional theory
- ▶ Advantage: don't have to make assumptions
- ▶ Disadvantages:
 - ▶ cannot leverage probability conclusions given distributional assumptions and statistical theory
 - ▶ results highly fit to the data
 - ▶ not really assumption-free, if we are honest

Correspondence Analysis

- ▶ CA is like factor analysis for categorical data
- ▶ Following normalization of the marginals, it uses Singular Value Decomposition to reduce the dimensionality of the word-by-text matrix
- ▶ This allows projection of the positioning of the words as well as the texts into multi-dimensional space
- ▶ The number of dimensions – as in factor analysis – can be decided based on the eigenvalues from the SVD

Correspondence Analysis contd.

- ▶ There are also problems with bootstrapping: (Milan and Whittaker 2004)
 - ▶ rotation of the principal components
 - ▶ inversion of singular values
 - ▶ reflection in an axis

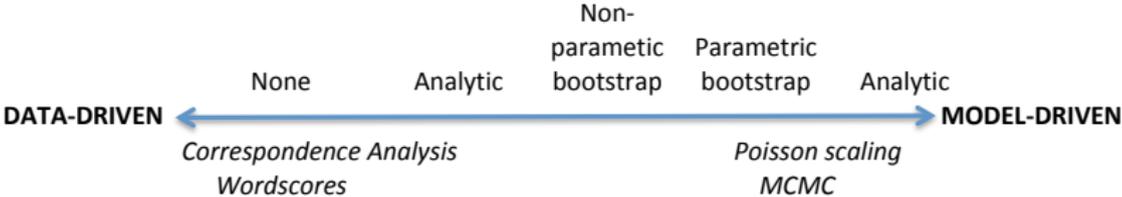
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Methods of uncertainty accounting in text scaling

	MCMC	Conditional ML	SVD-based	Algorithmic
Uncertainty accounting	(multinomial+)	(Poisson)	(CA)	(Wordscores)
Posterior sampling	✓			
Analytical		✓	??	?
Parametric bootstrap		✓		
Non-parametric BS		✓	?	✓

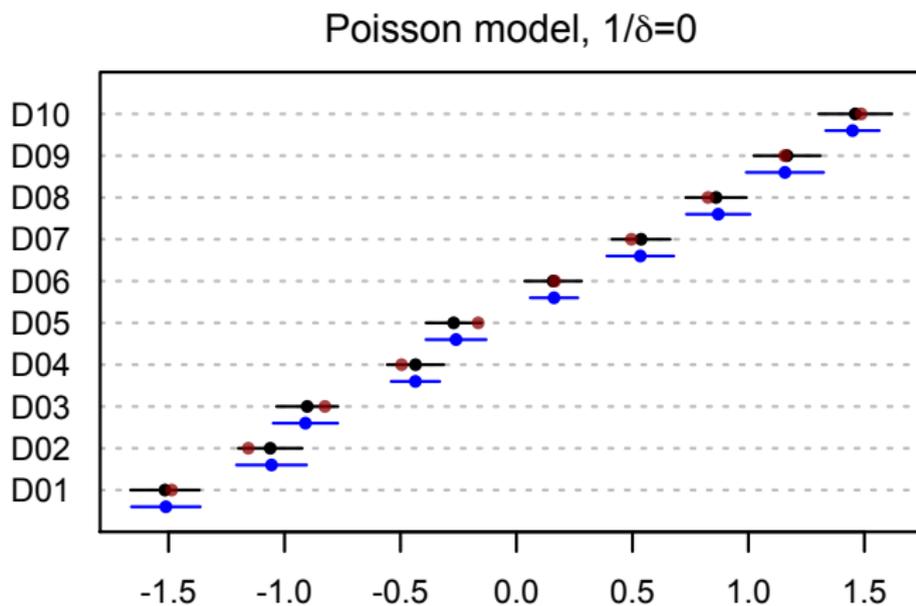
Data-driven versus parametric methods



Steps forward

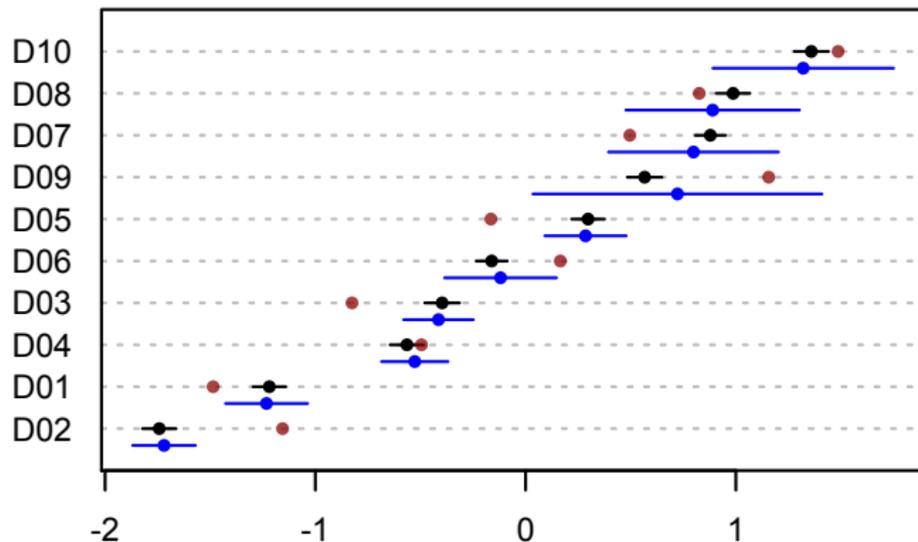
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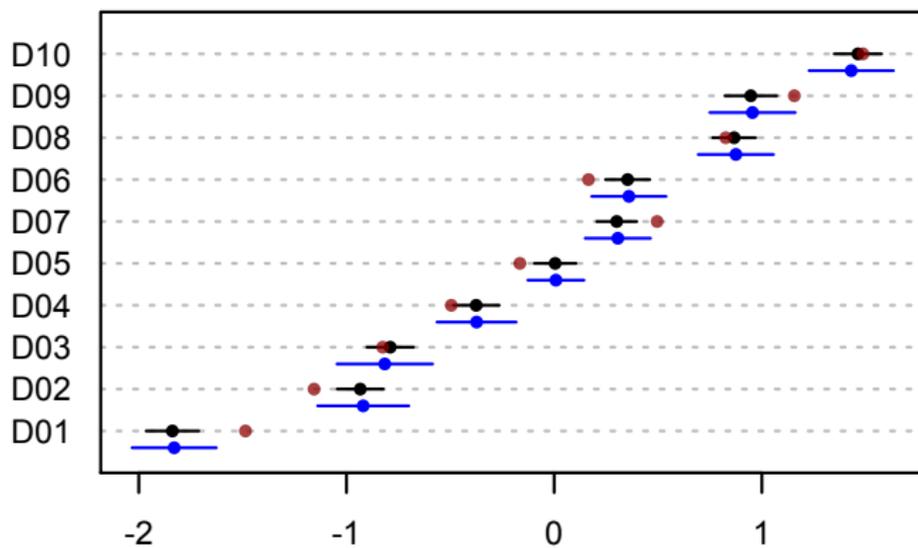
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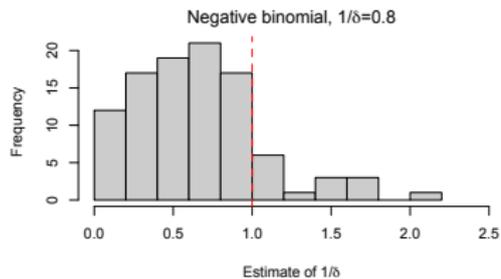
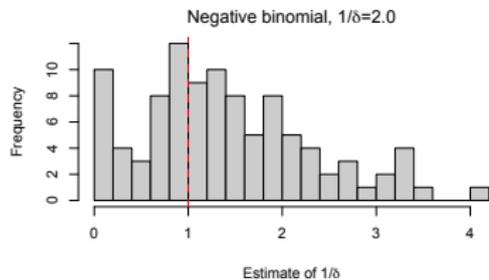
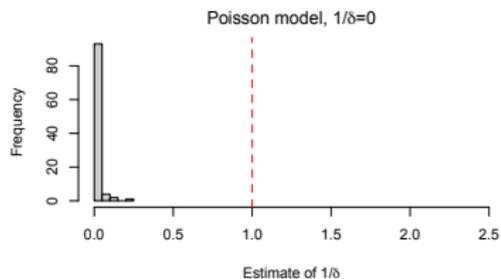


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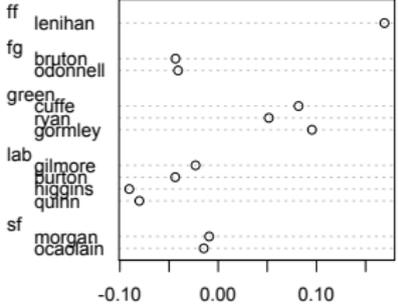
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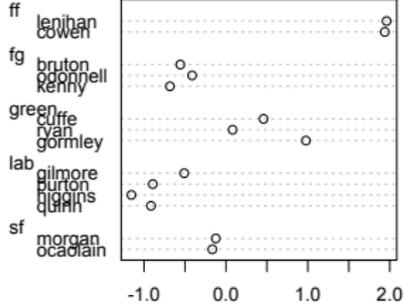
Simulated text results



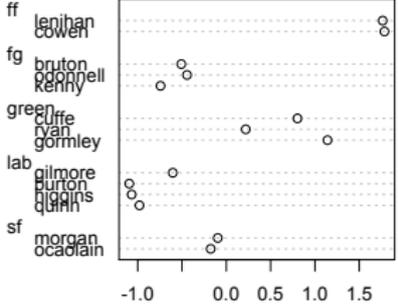
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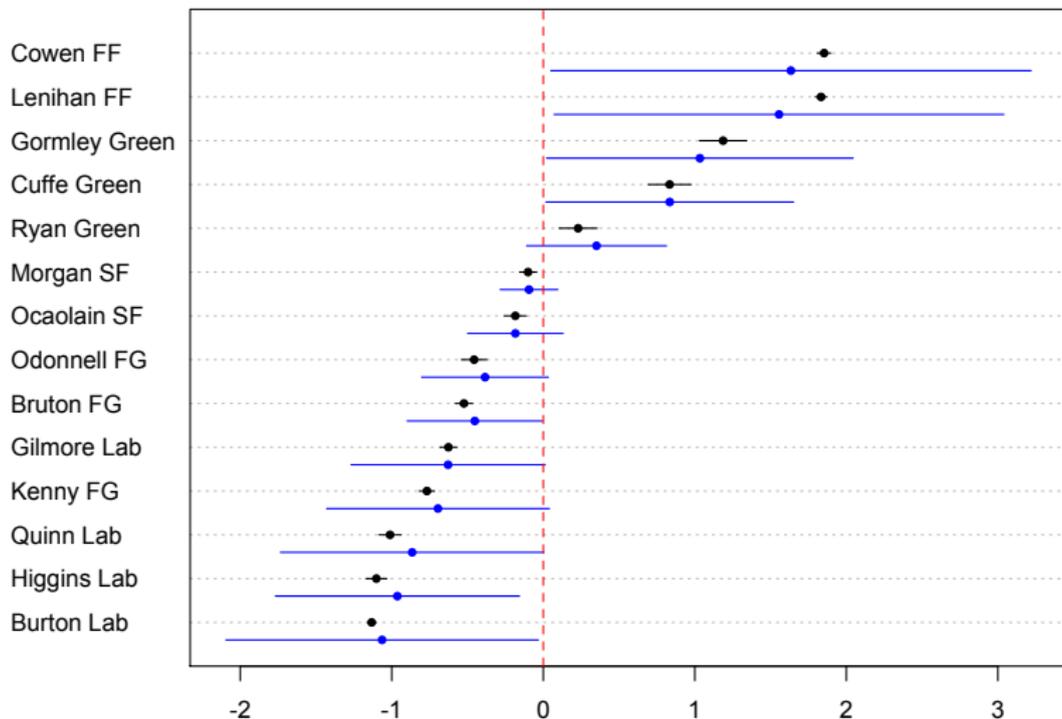
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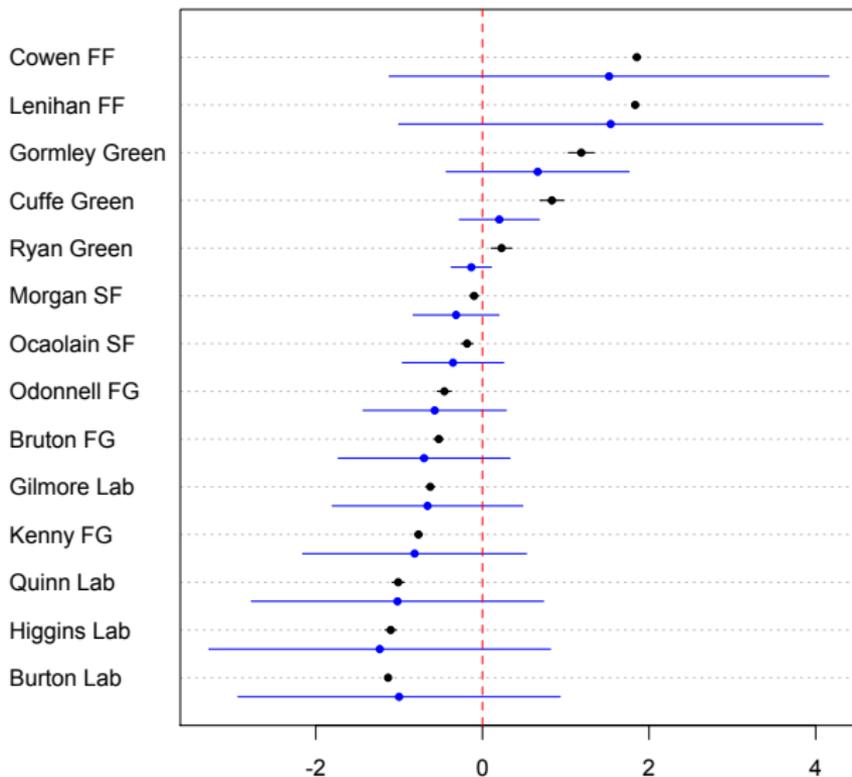
Budget debates: Analytical SEs

Non-parametric bootstrap (blue) versus Analytical SEs (black)



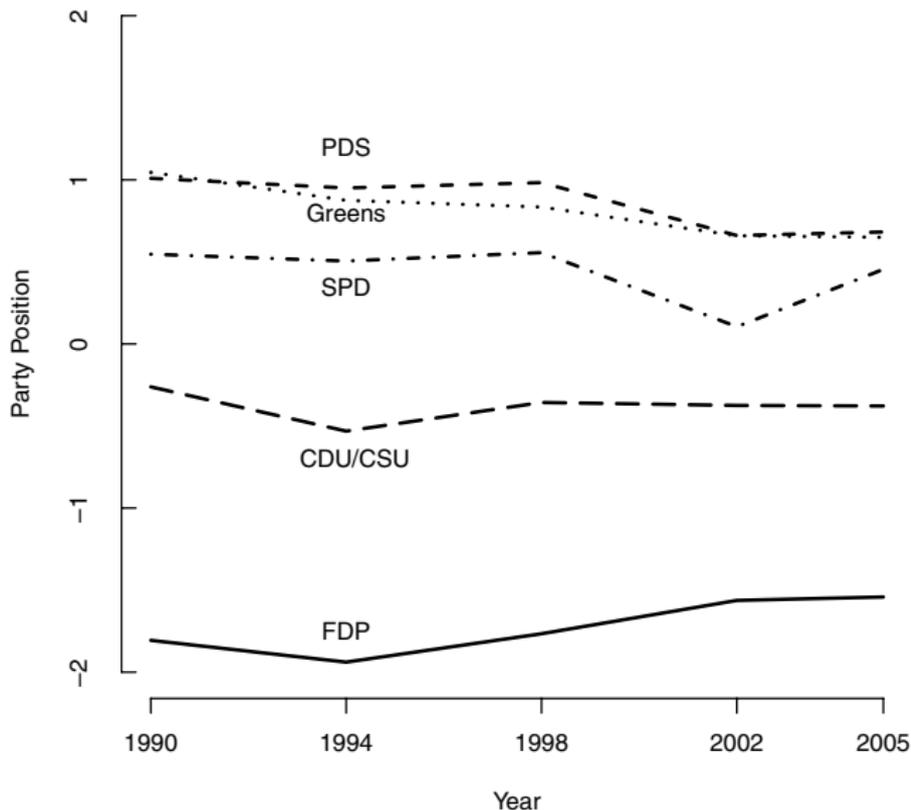
Budget debates: Bootstrapped SEs on CA

CA with non-parametric bootstrap (blue) versus Analytical SEs (black)



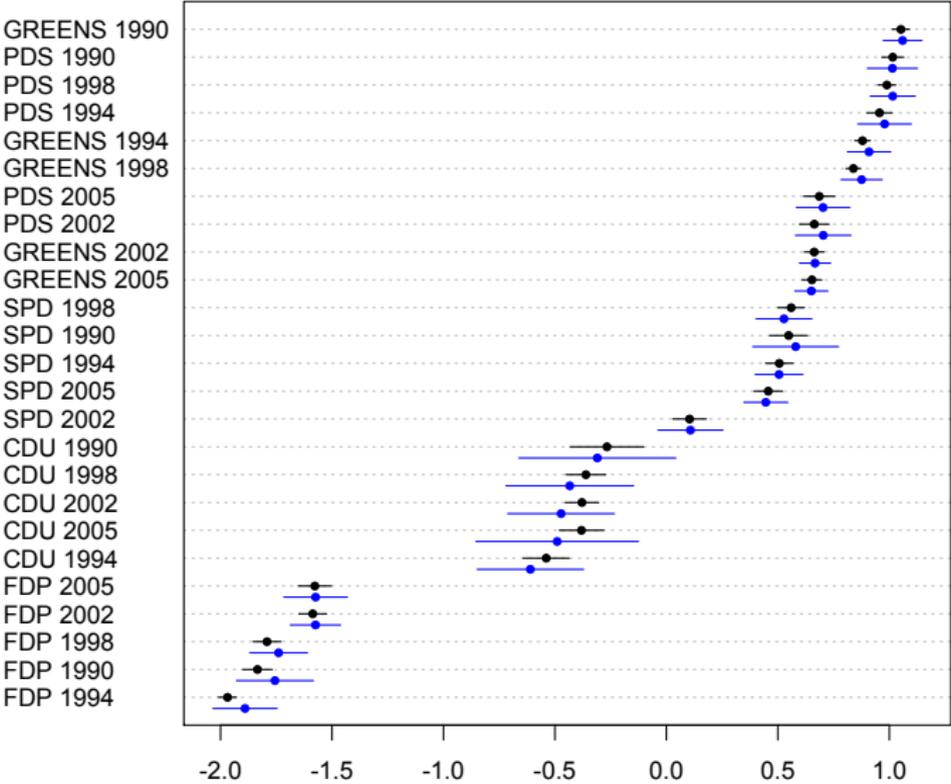
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German manifestos: Poisson Scaled Analytical SEs

Non-parametric bootstrap (blue) versus Analytical SEs (black)



German manifestos: Non-parametric bootstrap on CA

CA with non-parametric bootstrap (blue) versus Analytical SEs (black)

